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**Seo et al.**

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(45) **Date of Patent: Feb. 23, 2016**

(54) **EDGE BASED LOCATION FEATURE INDEX MATCHING**

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(22) Filed: **May 31, 2012**

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(51) **Int. Cl.**
***G06K 9/62*** (2006.01)
***G06K 9/46*** (2006.01)

(52) **U.S. Cl.**
CPC ..... ***G06K 9/6203*** (2013.01); ***G06K 9/4671*** (2013.01)

(58) **Field of Classification Search**
CPC ..... G06K 9/6203; G06K 9/6204; G06T 2207/10116; G06T 7/0081; G06T 7/0083; H04N 7/50; H04N 7/30
USPC ..... 382/209, 132, 232, 173, 199
See application file for complete search history.

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Alexander Sibiryakov, "Fast and High-Performance Template Matching Method," IEEE CVPR, 2011, 8 pgs.
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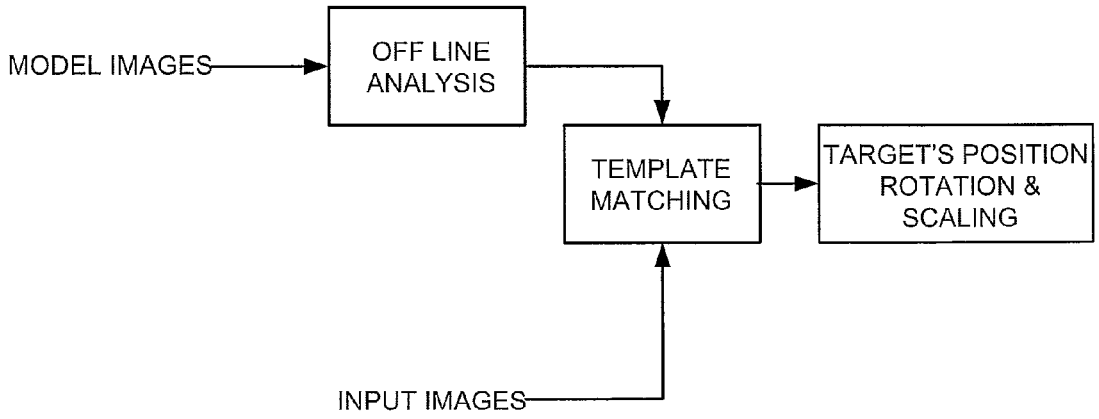
(57) **ABSTRACT**

A system for image processing that matches a model image with an input image. The matching process includes using a feature location index for the model image.

**14 Claims, 22 Drawing Sheets**




**TEMPLATE MATCHING**

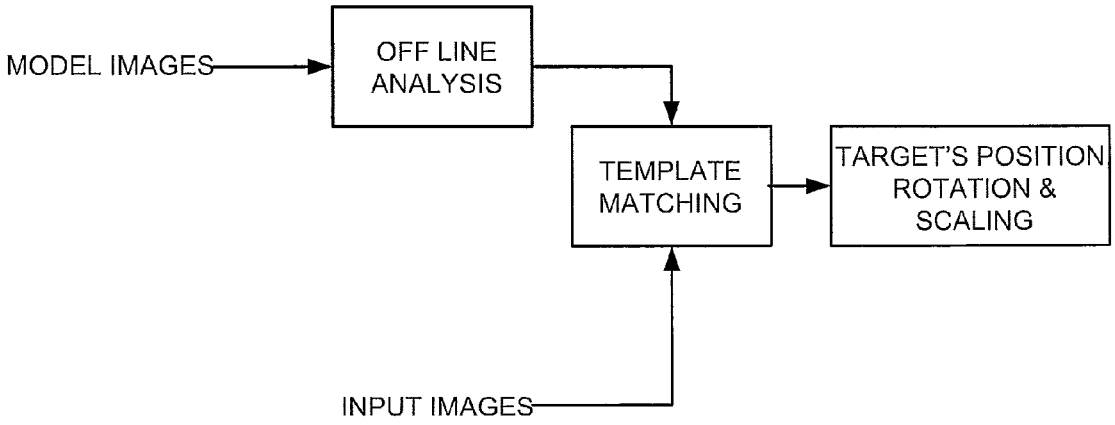
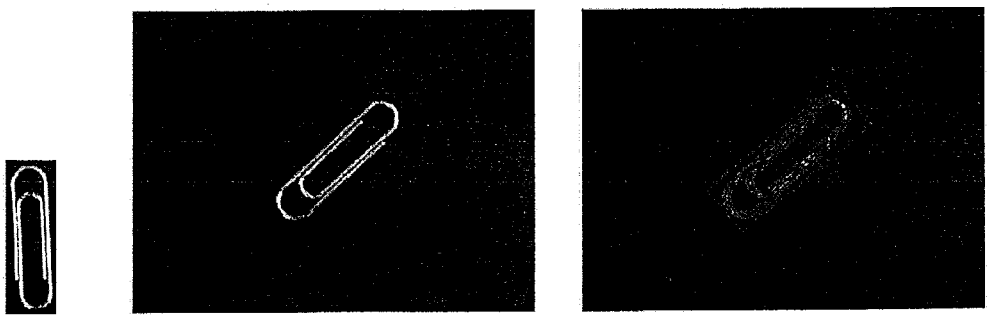



**FIG. 1**
**TEMPLATE MATCHING**

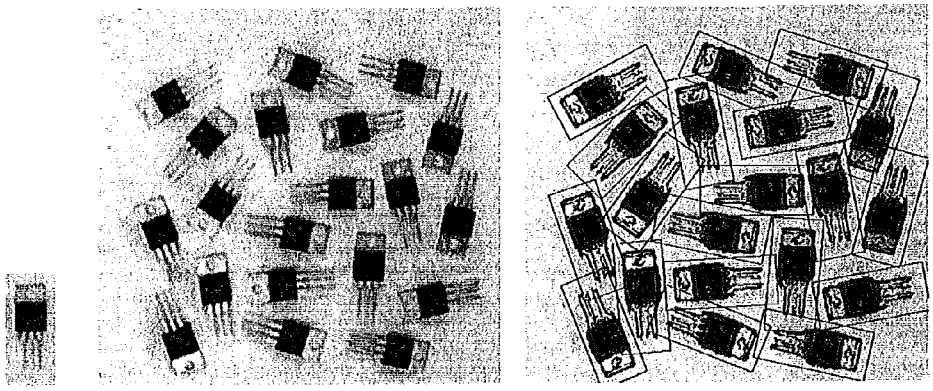


model image

example input image

example output image

FIG. 2



model image

example input image

example output image

FIG. 3

FIG. 4

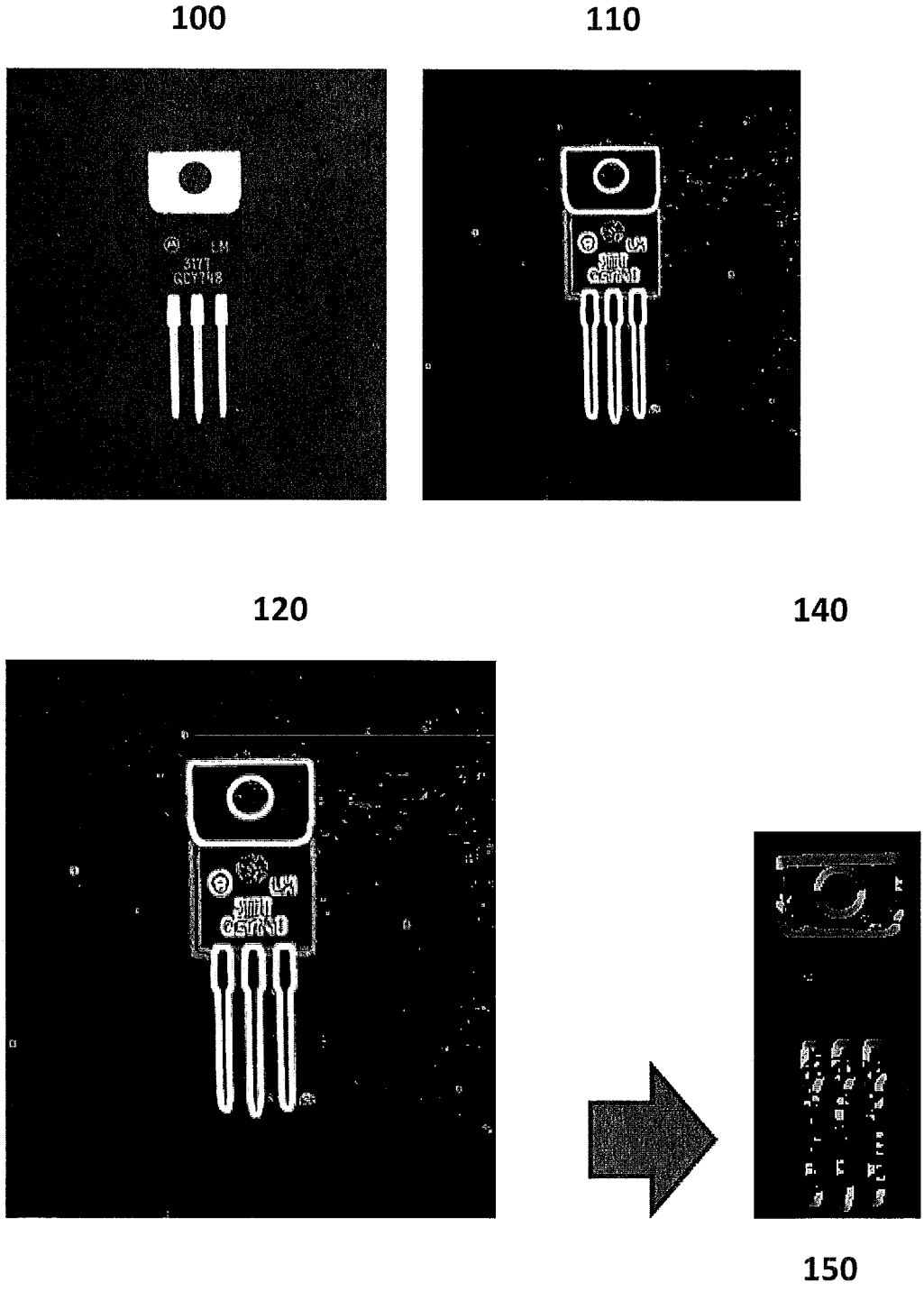



FIG. 5

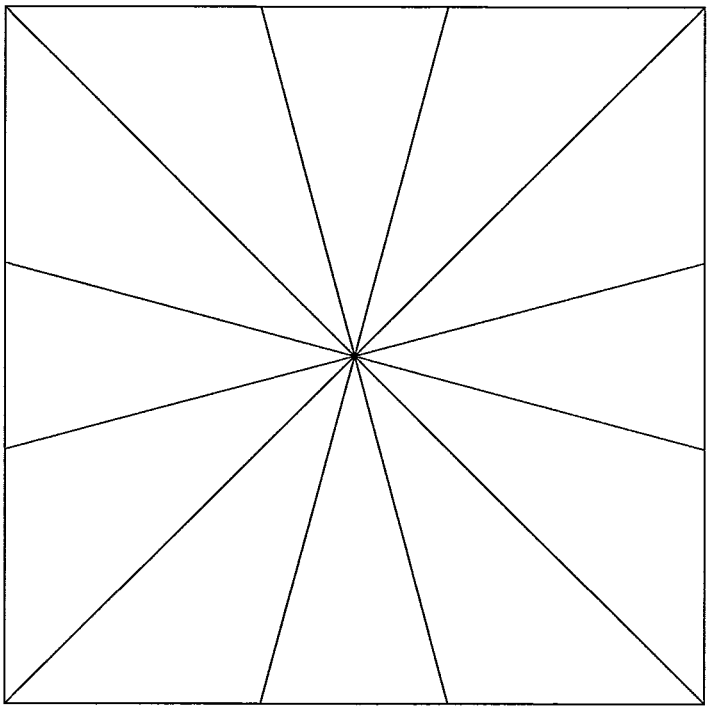


FIG. 6

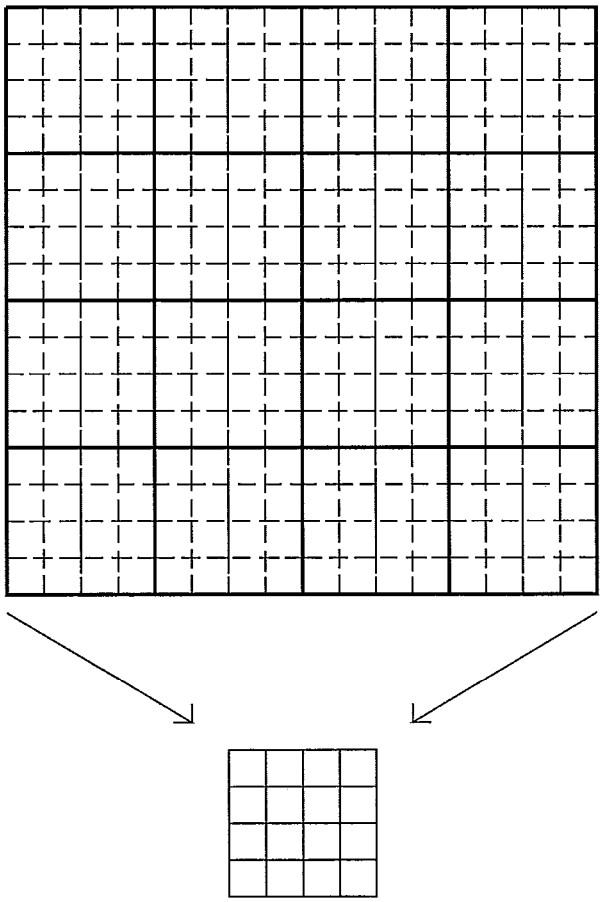


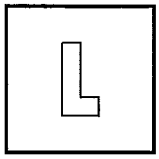
FIG. 7

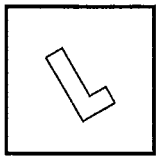
| INDEX | ANGULAR RANGE | BIT PATTERN |
|---|---|---|
| 0 | NON-EDGE | 00000000 |
| 1 | -15 to +15 | 00000010 |
| 2 | +15 to +45 | 00000100 |
| 3 | +45 to +75 | 00001000 |
| 4 | +75 to +105 | 00010000 |
| 5 | +105 to +135 | 00100000 |
| 6 | +135 to +165 | 01000000 |
| 7 | NOT USED | 00000000 |

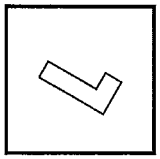
FIG. 8

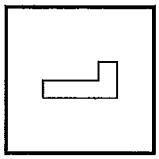
| INDEX | ANGULAR RANGE | BIT PATTERN |
|---|---|---|
| 0 | NON-EDGE | 00000000 |
| 1 | -15 to +15 | 01000110 |
| 2 | +15 to +45 | 00001110 |
| 3 | +45 to +75 | 00011100 |
| 4 | +75 to +105 | 00111000 |
| 5 | +105 to +135 | 01110000 |
| 6 | +135 to +165 | 01100010 |
| 7 | NOT USED | 00000000 |

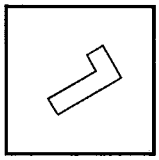
FIG. 9

0 DEGREE TEMPLATE 

30 DEGREE TEMPLATE 

60 DEGREE TEMPLATE 

90 DEGREE TEMPLATE 

120 DEGREE TEMPLATE 

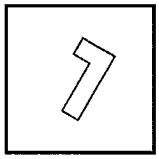
150 DEGREE TEMPLATE 

FIG. 10

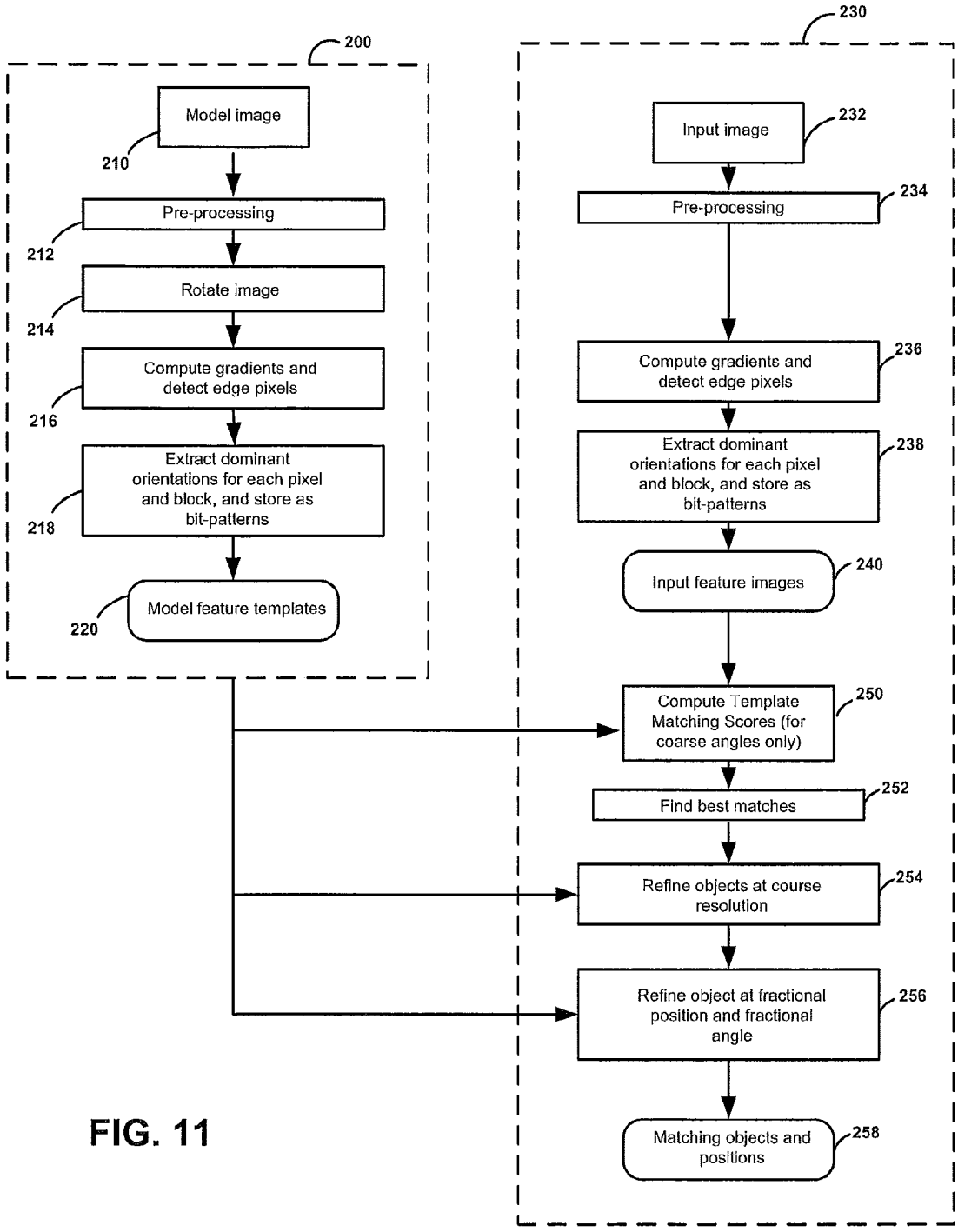

200
Model image
210
Pre-processing
212
Rotate image
214
Compute gradients and detect edge pixels
216
Extract dominant orientations for each pixel and block, and store as bit-patterns
218
Model feature templates
220
230
Input image
232
Pre-processing
234
Compute gradients and detect edge pixels
236
Extract dominant orientations for each pixel and block, and store as bit-patterns
238
Input feature images
240
Compute Template Matching Scores (for coarse angles only)
250
Find best matches
252
Refine objects at course resolution
254
Refine object at fractional position and fractional angle
256
Matching objects and positions
258

FIG. 11

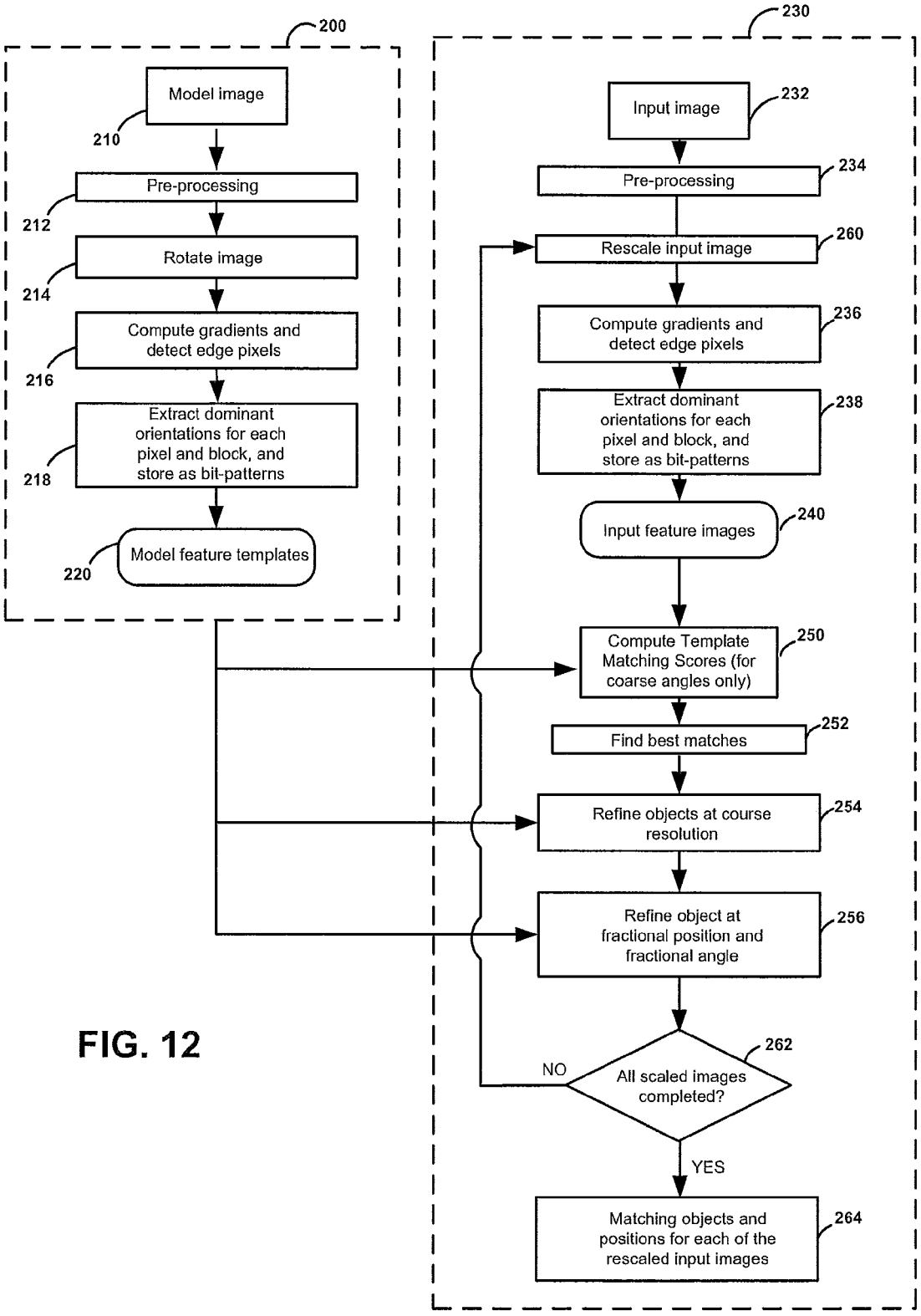

200
Model image
210
Pre-processing
212
Rotate image
214
Compute gradients and detect edge pixels
216
Extract dominant orientations for each pixel and block, and store as bit-patterns
218
Model feature templates
220
230
Input image
232
Pre-processing
234
Rescale input image
260
Compute gradients and detect edge pixels
236
Extract dominant orientations for each pixel and block, and store as bit-patterns
238
Input feature images
240
Compute Template Matching Scores (for coarse angles only)
250
Find best matches
252
Refine objects at course resolution
254
Refine object at fractional position and fractional angle
256
All scaled images completed?
262
NO
YES
Matching objects and positions for each of the rescaled input images
264

FIG. 12

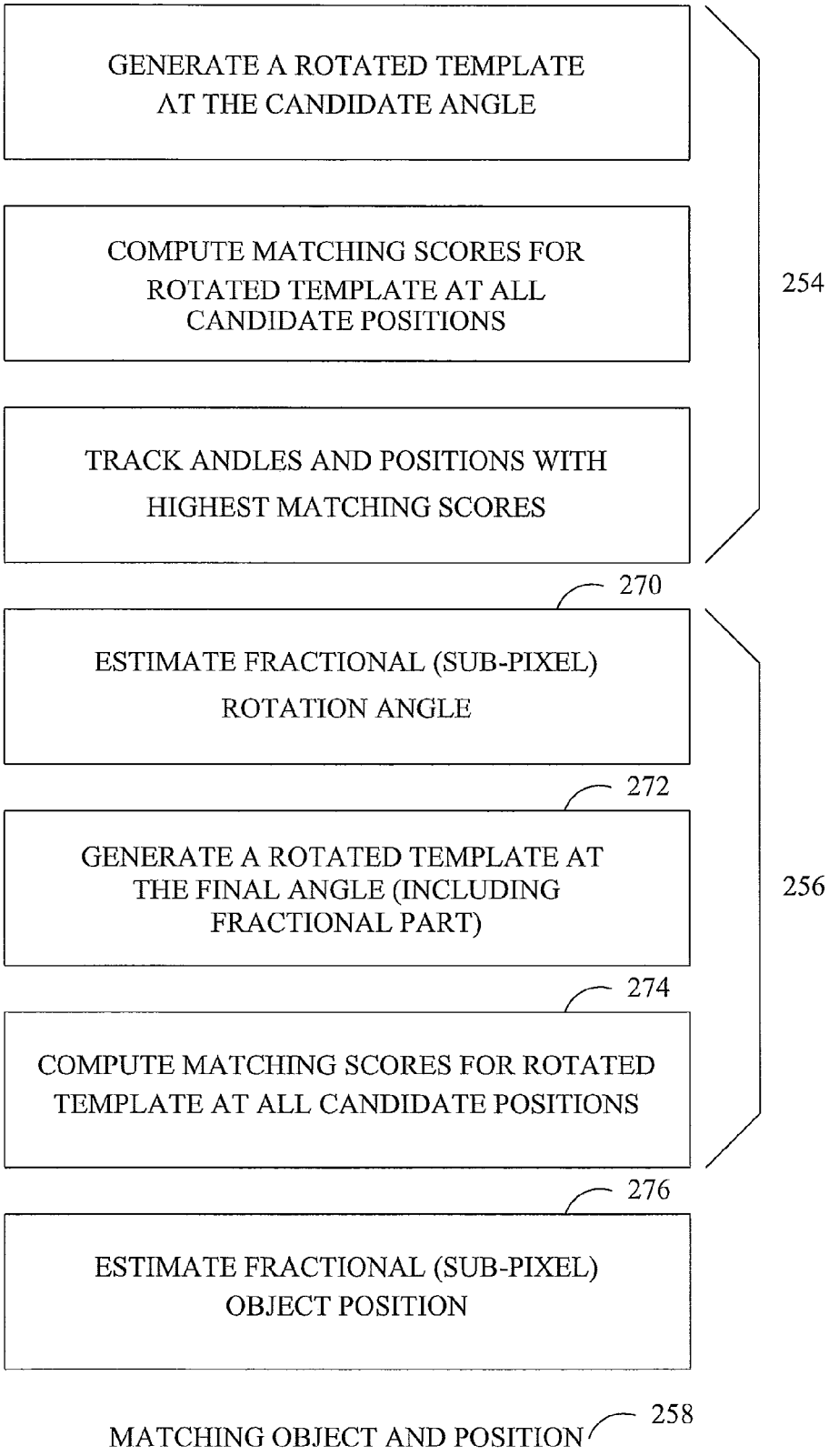

GENERATE A ROTATED TEMPLATE AT THE CANDIDATE ANGLE
COMPUTE MATCHING SCORES FOR ROTATED TEMPLATE AT ALL CANDIDATE POSITIONS
TRACK ANDLES AND POSITIONS WITH HIGHEST MATCHING SCORES
254
270
ESTIMATE FRACTIONAL (SUB-PIXEL) ROTATION ANGLE
272
GENERATE A ROTATED TEMPLATE AT THE FINAL ANGLE (INCLUDING FRACTIONAL PART)
274
COMPUTE MATCHING SCORES FOR ROTATED TEMPLATE AT ALL CANDIDATE POSITIONS
256
276
ESTIMATE FRACTIONAL (SUB-PIXEL) OBJECT POSITION
MATCHING OBJECT AND POSITION
258

FIG. 13

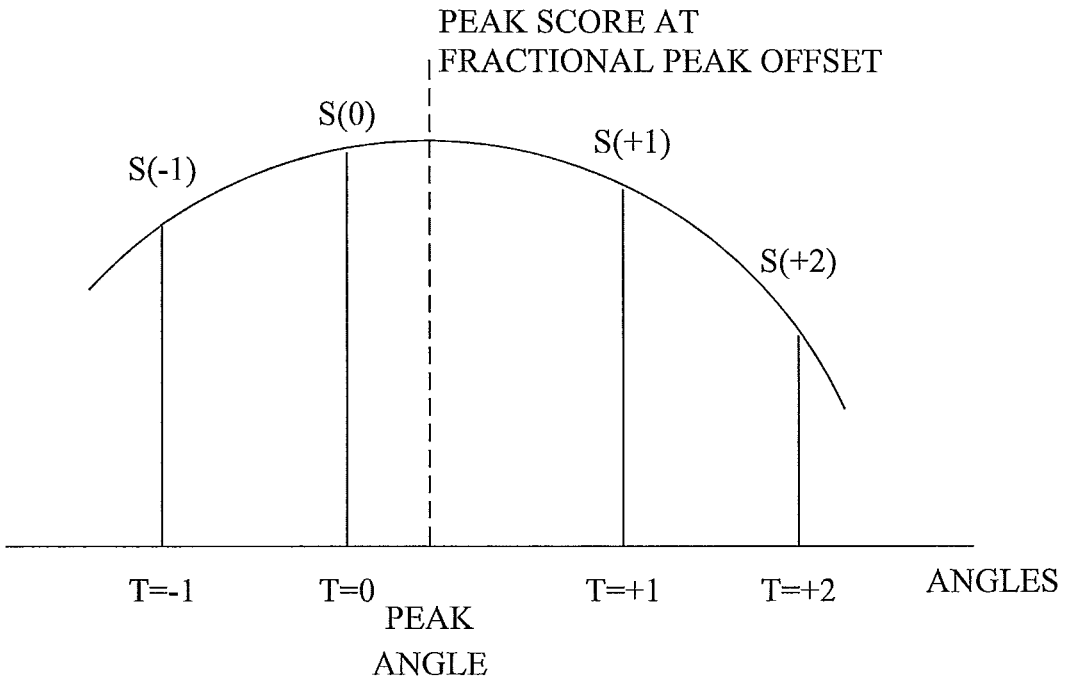

PEAK SCORE AT
FRACTIONAL PEAK OFFSET
S(0)
S(-1)
S(+1)
S(+2)
T=-1
T=0
T=+1
T=+2
ANGLES
PEAK
ANGLE

FIG. 14

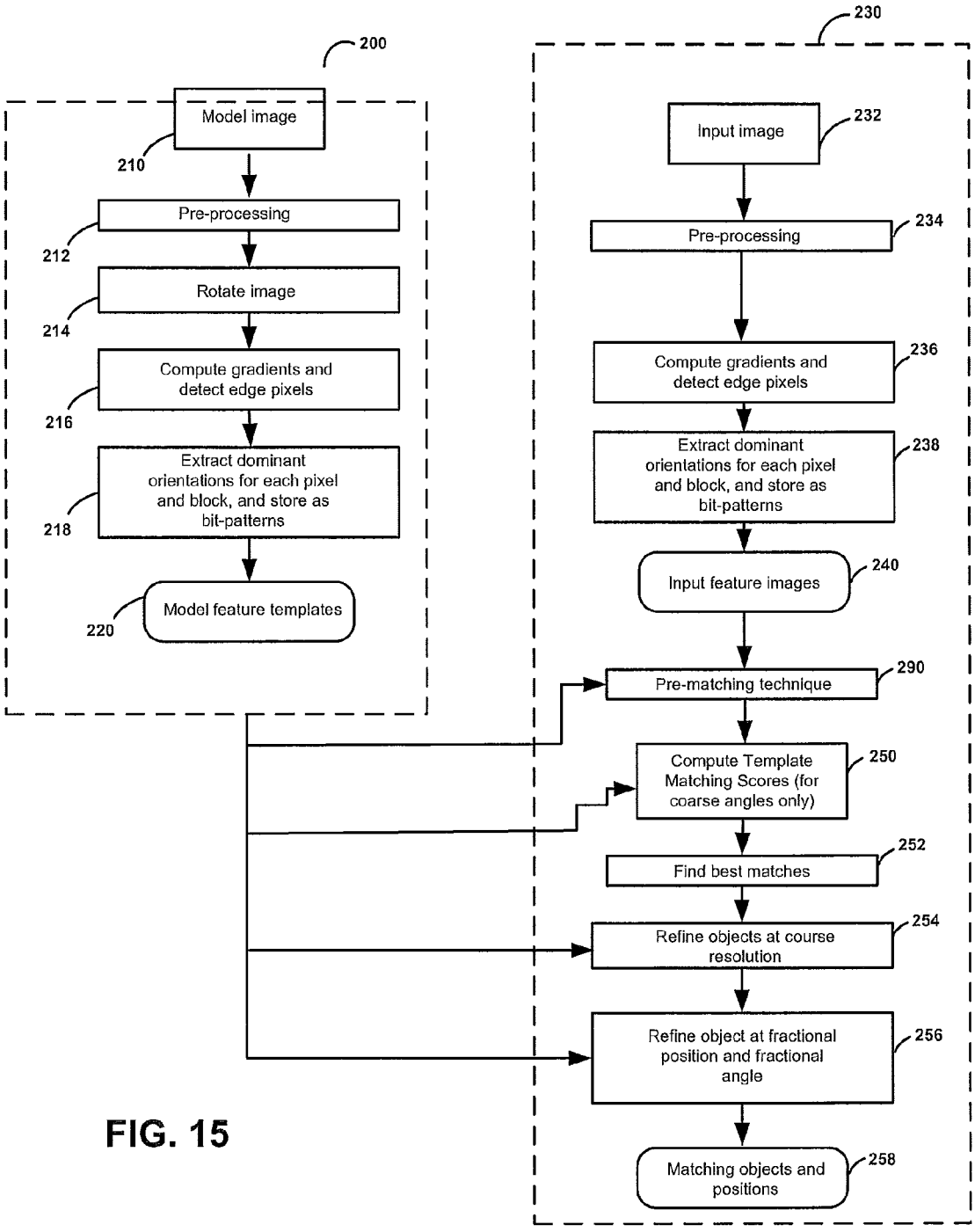

200
Model image
210
Pre-processing
212
Rotate image
214
Compute gradients and detect edge pixels
216
Extract dominant orientations for each pixel and block, and store as bit-patterns
218
Model feature templates
220
230
Input image
232
Pre-processing
234
Compute gradients and detect edge pixels
236
Extract dominant orientations for each pixel and block, and store as bit-patterns
238
Input feature images
240
Pre-matching technique
290
Compute Template Matching Scores (for coarse angles only)
250
Find best matches
252
Refine objects at course resolution
254
Refine object at fractional position and fractional angle
256
Matching objects and positions
258

FIG. 15

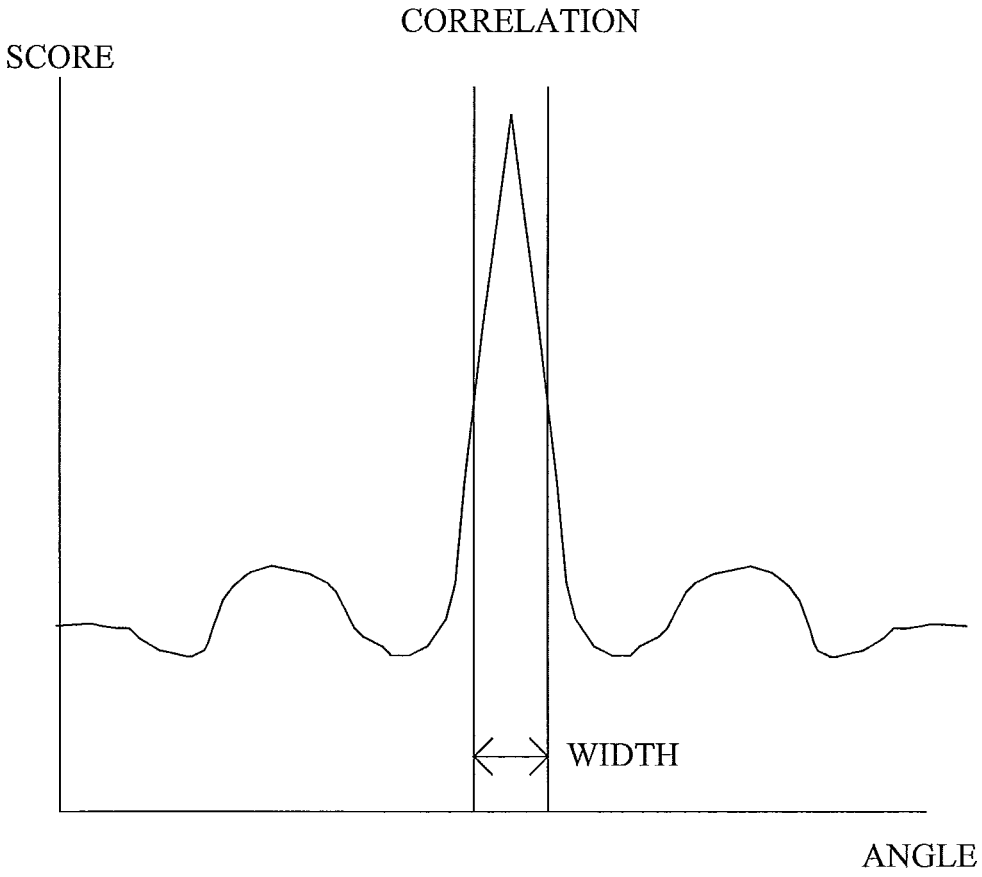



FIG. 16

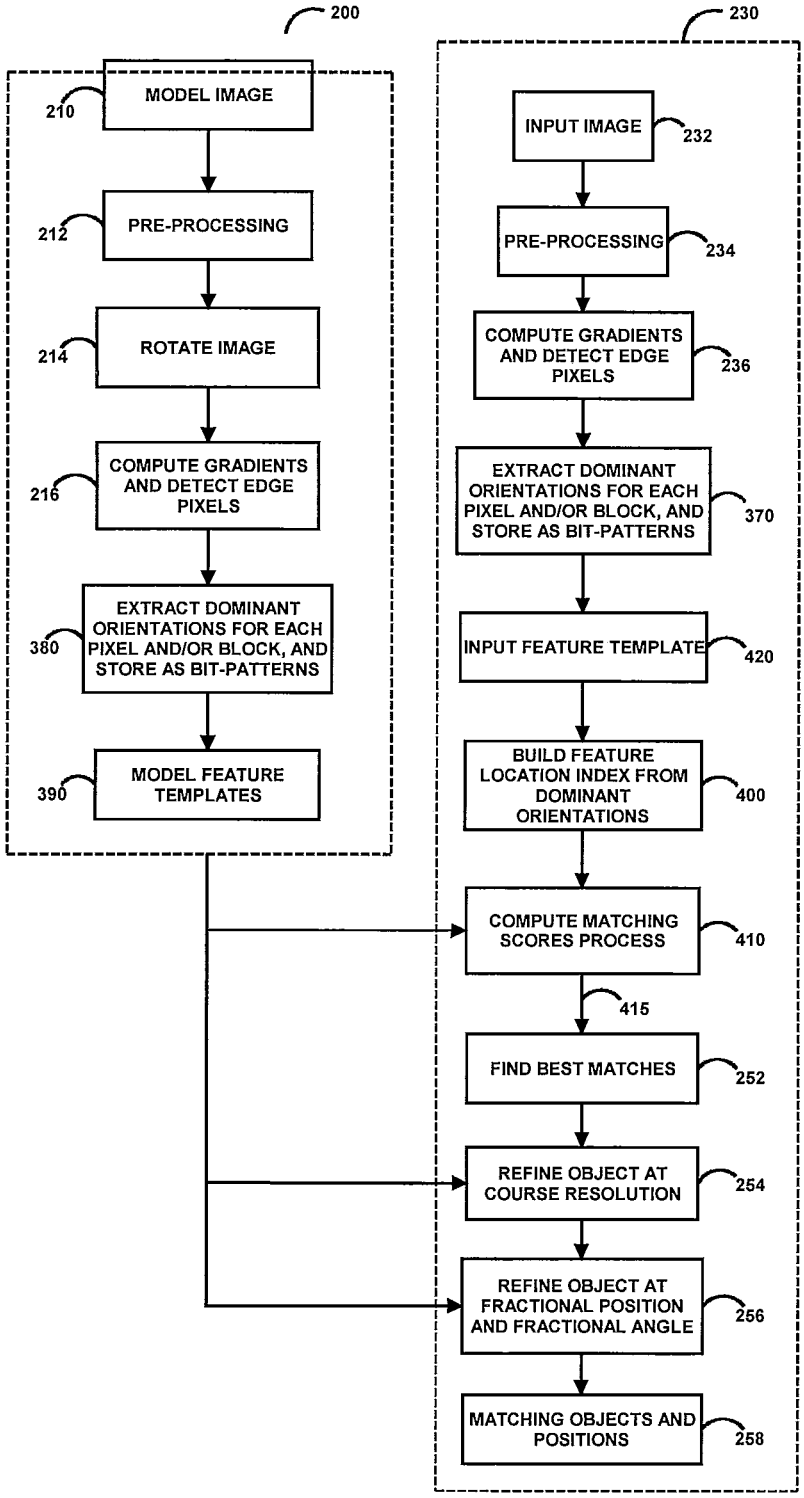

200
MODEL IMAGE
210
PRE-PROCESSING
212
ROTATE IMAGE
214
COMPUTE GRADIENTS AND DETECT EDGE PIXELS
216
EXTRACT DOMINANT ORIENTATIONS FOR EACH PIXEL AND/OR BLOCK, AND STORE AS BIT-PATTERNS
380
MODEL FEATURE TEMPLATES
390
230
INPUT IMAGE
232
PRE-PROCESSING
234
COMPUTE GRADIENTS AND DETECT EDGE PIXELS
236
EXTRACT DOMINANT ORIENTATIONS FOR EACH PIXEL AND/OR BLOCK, AND STORE AS BIT-PATTERNS
370
INPUT FEATURE TEMPLATE
420
BUILD FEATURE LOCATION INDEX FROM DOMINANT ORIENTATIONS
400
COMPUTE MATCHING SCORES PROCESS
410
415
FIND BEST MATCHES
252
REFINE OBJECT AT COURSE RESOLUTION
254
REFINE OBJECT AT FRACTIONAL POSITION AND FRACTIONAL ANGLE
256
MATCHING OBJECTS AND POSITIONS
258

FIG. 17

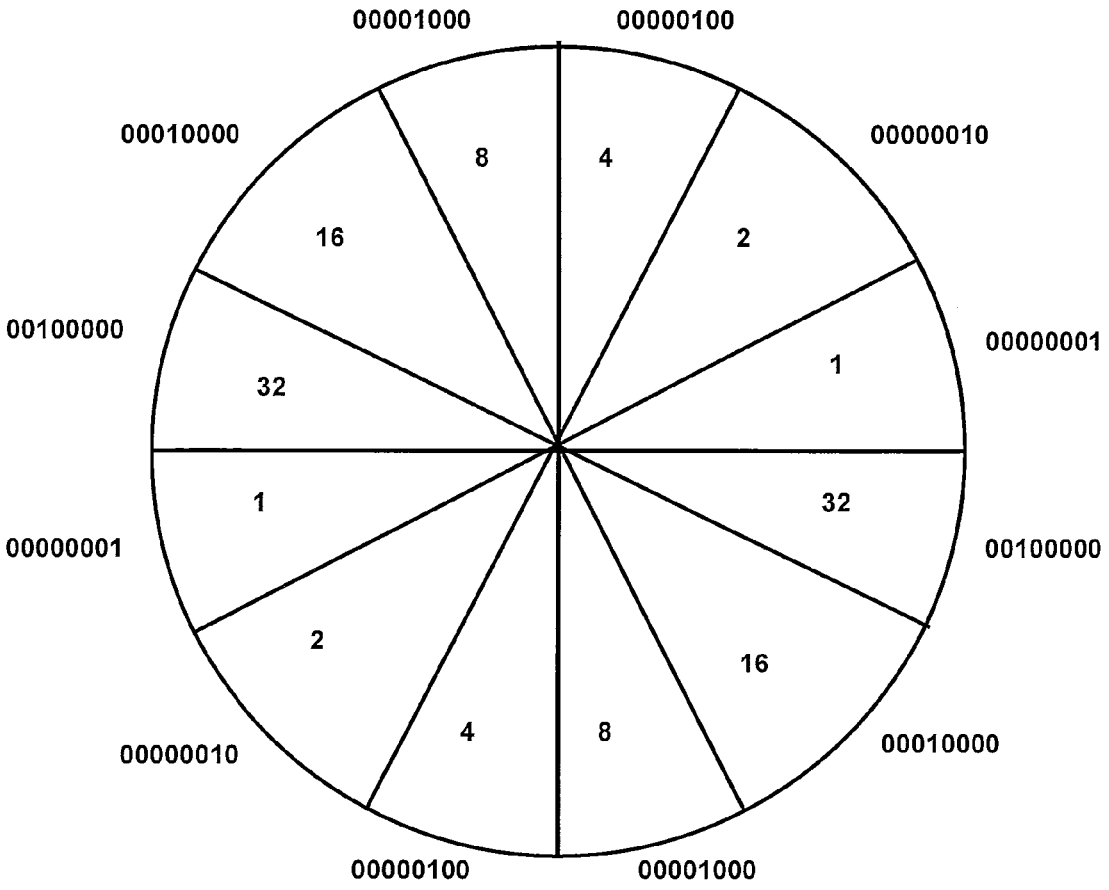

00001000
00000100
00010000
00000010
00100000
00000001
00000001
00100000
00000010
00010000
00000100
00001000
8
4
16
2
32
1
1
32
2
16
4
8

FIG. 18

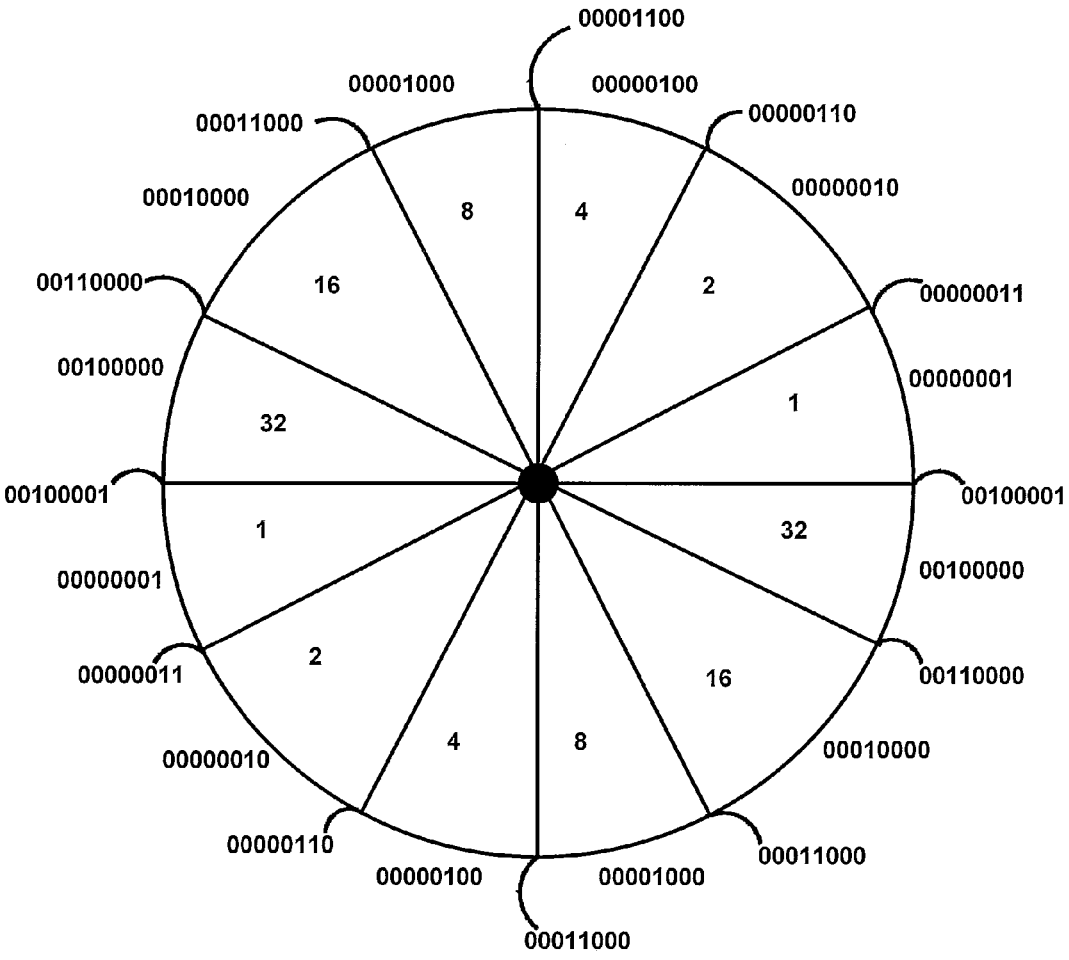

00001100
00000100
00000110
00000010
00000011
00000001
00100001
00100000
00110000
00010000
00011000
00001000
00000100
00000110
00000010
00000011
00000001
00100001
00100000
00110000
00010000
00011000
00001000
8
4
2
1
32
16
1
32
16
2
4
8

FIG. 19

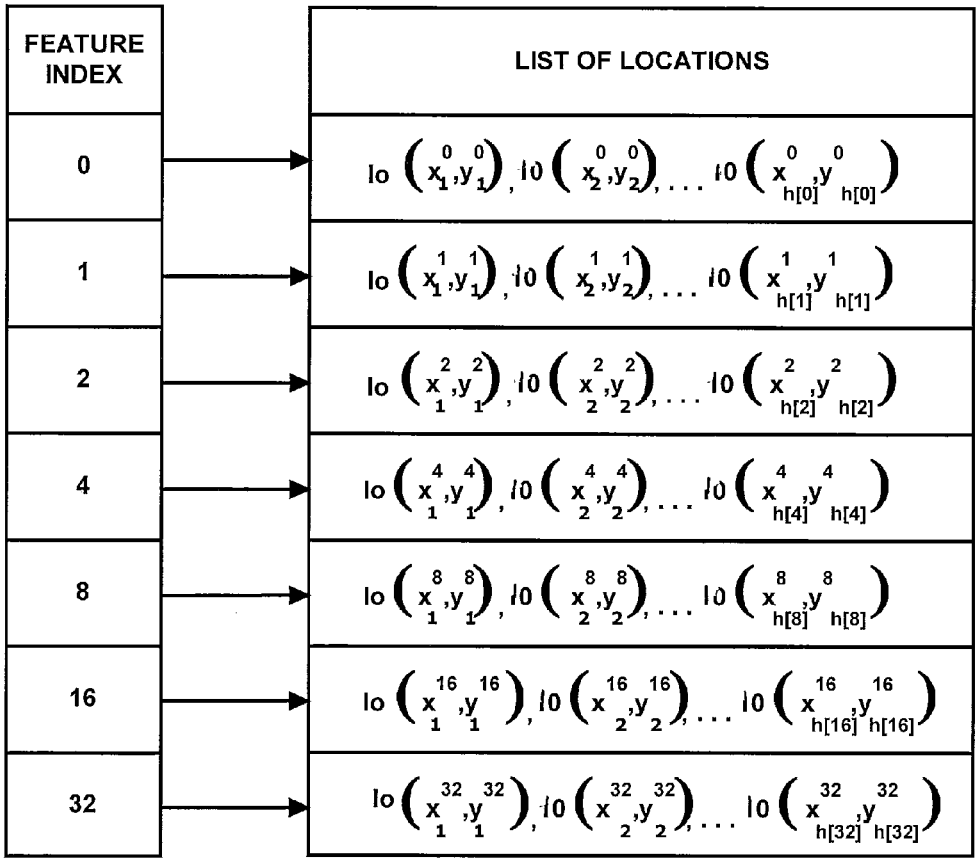



FIG. 20

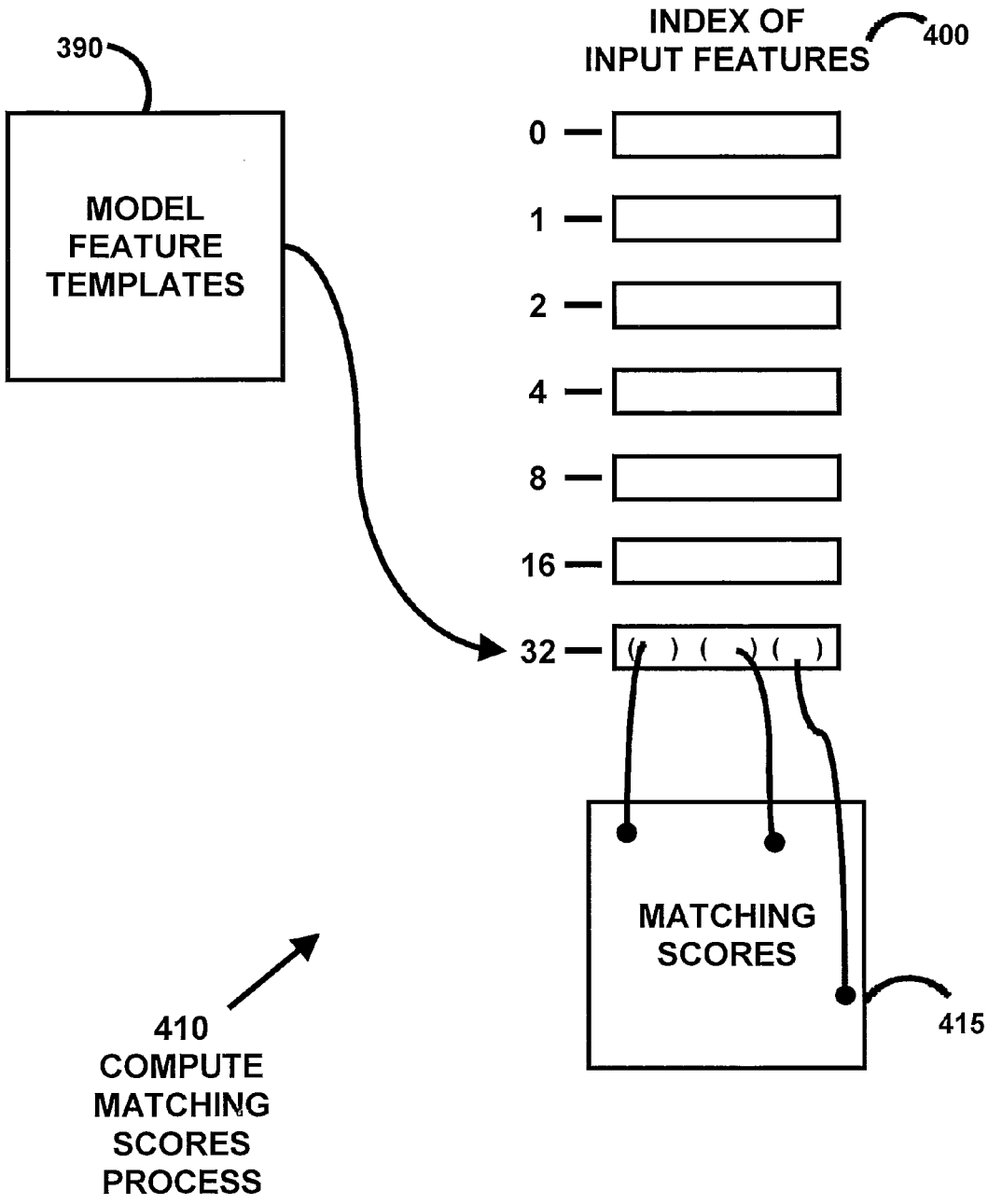

390
MODEL FEATURE TEMPLATES
INDEX OF INPUT FEATURES
400
0
1
2
4
8
16
32
MATCHING SCORES
415
410
COMPUTE MATCHING SCORES PROCESS

FIG. 21

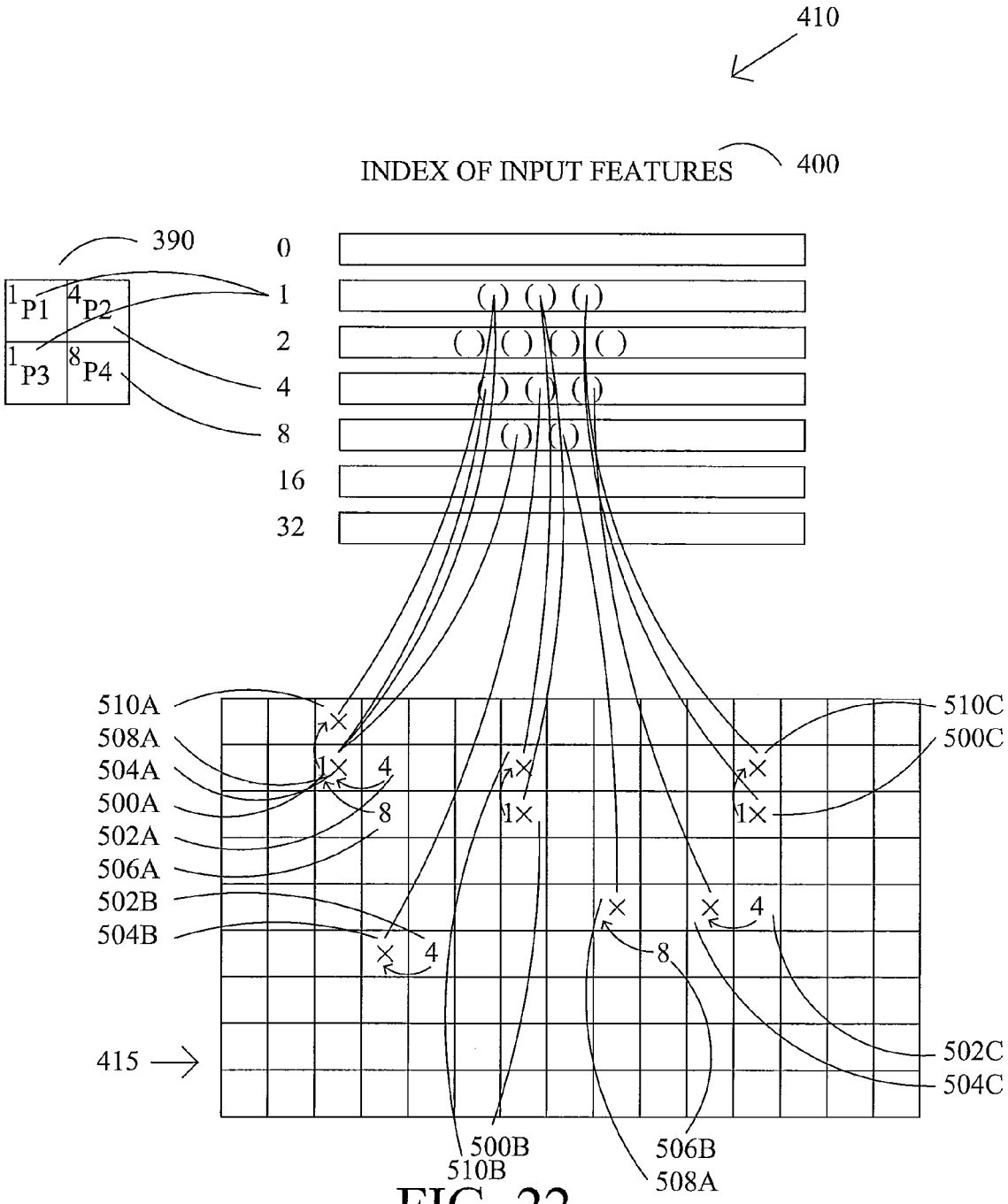

410
INDEX OF INPUT FEATURES
400
390
1 P1
4 P2
1 P3
8 P4
0
1
2
4
8
16
32
510A
508A
504A
500A
502A
506A
502B
504B
415
510C
500C
502C
504C
500B
510B
506B
508A

FIG. 22

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 3 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

FIG. 23

# EDGE BASED LOCATION FEATURE INDEX MATCHING

## CROSS-REFERENCE TO RELATED APPLICATIONS

None.

## BACKGROUND OF THE INVENTION

The present invention relates generally to template matching for an image.

Referring to FIG. **1**, template matching is a commonly used technique in order to recognize content in an image. The template matching technique includes a given target object in a model image, automatically finding the position, orientation, and scaling of the target object in input images. Generally, the input images undergo geometric transforms (rotation, zoom, etc) and photometric changes (brightness/contrast changes, blur, noise, etc). In the context of template matching, the relevant characteristics of the target object in the model image may be assumed to be known before the template matching to the target image is performed. Such characteristics of the target object may be extracted, modeled, and learned previously in a manner that may be considered "off-line," while the matching of those characteristics to the input image may be considered "on-line."

One of the template matching techniques includes feature point based template matching which achieves good matching accuracy. Feature point based template matching extracts object discriminative interesting points and features from the model and the input images. Then those features are matched between the model image and the input image with K-nearest neighbor search or some feature point classification technique. Next a homography transformation is estimated from those matched feature points, which may further be refined.

Feature point based template matching works well when objects contain a sufficient number of interesting feature points. It typically fails to produce a valid homography when the target object in the input or model image contains few or no interesting points (e.g. corners), or the target object is very simple (e.g. target object consists of only edges, like paper clip) or symmetric, or the target object contains repetitive patterns (e.g. machine screw). In these situations, too many ambiguous matches prevents generating a valid homography. To reduce the likelihood of such failure, global information of the object such as edges, contours, or shape may be utilized instead of merely relying on local features.

Another category of template matching is to search the target object by sliding a window of the reference template in a pixel-by-pixel manner, and computing the degree of similarity between them, where the similarity metric is commonly given by correlation or normalized cross correlation. Pixel-by-pixel template matching is very time-consuming and computationally expensive. For an input image of size N×N and the model image of size W×W, the computational complexity is $O(W^2 \times N^2)$, given that the object orientation in both the input and model image is coincident. When searching for an object with arbitrary orientation, one technique is to do template matching with the model image rotated in every possible orientation, which makes the matching scheme far more computationally expensive. To reduce the computation time, coarse-to-fine, multi-resolution template matching may be used.

What is desired therefore is a computationally efficient edge based matching technique.



The foregoing and other objectives, features, and advantages of the invention may be more readily understood upon consideration of the following detailed description of the invention, taken in conjunction with the accompanying drawings.

## BRIEF DESCRIPTION OF THE SEVERAL VIEWS OF THE DRAWINGS

FIG. **1** illustrates template matching.

FIG. **2** illustrates a model image, an input image, and an output image.

FIG. **3** illustrates another model image, an input image, and an output image.

FIG. **4** illustrates another model image, an input image, and an output image.

FIG. **5** illustrates an image matching technique.

FIG. **6** illustrates a plurality of angular orientations.

FIG. **7** illustrates pixel blocks of an image.

FIG. **8** illustrates a bit pattern for different angles.

FIG. **9** illustrates another bit pattern for different angles.

FIG. **10** illustrates a plurality of templates at different rotations.

FIG. **11** illustrates an image processing technique for matching.

FIG. **12** illustrates an image processing technique for matching that includes scaling.

FIG. **13** illustrates a refinement technique for image matching.

FIG. **14** illustrates a fractional peak offset.

FIG. **15** illustrates an image processing technique for matching that includes pre-filtering.

FIG. **16** illustrates a correction of different angles together with a threshold.

FIG. **17** illustrates a modified image processing technique for matching.

FIG. **18** illustrates a set of angular orientations for image features.

FIG. **19** illustrates another set of angular orientations for image features.

FIG. **20** illustrates a feature location index.

FIG. **21** illustrates the computation of matching scores.

FIG. **22** illustrates a more detailed computation of matching scores.

FIG. **23** illustrates accumulated matching scores.

## DETAILED DESCRIPTION OF PREFERRED EMBODIMENT

Referring to FIG. **2**, in many cases a model image has a limited set of feature points but tends to have relatively sharp edge features. One such example is a paperclip. Then using a suitable matching technique it is desirable to find a matching object in one or more input images, in a computationally efficient manner. The matching object may be at an unknown position and at an unknown rotation.

Referring to FIG. **3**, in many cases the input image may have one or more matching objects of interest, which may be overlapping with one another. Then using a suitable matching technique it is desirable to find matching objects in one or more input images, in a computationally efficient manner. The matching objects may be at an unknown position and at an unknown rotation.

Referring to FIG. **4**, in many cases the input image may have one or more matching objects of interest, which may be overlapping with one another. Then using a suitable matching technique it is desirable to find matching objects in one or

more input images, in a computationally efficient manner. The matching object may be at an unknown position, unknown rotation, and unknown scale.

Referring again to FIG. **2**, FIG. **3**, and FIG. **4**, the matching technique should be computationally efficient, while being sufficiently robust to distinguish image features such as sharp corners, significant edges, or distinguish images with relatively few such features. Moreover, the matching technique should be sufficiently robust to reduce effects due to lighting or illumination changes in the image, blur in the image, noise in the image, and other imaging imperfections. Also, the matching technique should be sufficiently robust to be tolerant to partial occlusions of the object or missing parts of the object in the input image.

Referring to FIG. **5**, a model image **100** may be received by the system. A preferred technique to determine regions of the model image **100** that are likely to be of interest for image matching is to use an edge based technique **110** to locate edges of the model image. For example, one way to determine the edges **110** is to use a gradient based technique. Edge based techniques are generally robust, generally invariant to lighting changes, generally invariant to illumination changes, generally noise resistant, and generally may be implemented in a computationally efficient manner. For each of the pixels determined to be an edge pixel, the orientation of the edge **120** may be determined. For example, the orientation **120** at each edge pixel may be determined to have an orientation from 0 to 179 degrees (e.g., less than 360 degrees), such as in one degree increments. The orientation may be a full 360 degrees, if desired. The edge orientation **120** therefore preferably includes information regarding the alignment of the edge, but not its particular direction. To increase the invariance of the technique, the edge orientation **120** is preferably defined in a range of generally 180 degrees (e.g., less than 360 degrees). In this manner, the direction of an edge may be either in one direction (e.g., north) or the opposite direction (e.g., south), but the system is agnostic as to which particular direction. This manner of edge orientation characterization results in a system that is more invariant to contrast inversions.

A pixel resolution template **140** may be determined based upon the edge orientations **120**. The pixel resolution template **140** may have 180 degrees of angular information at one degree increments (or some other suitable angular increment) at each of the edge pixel locations. Processing input images based only upon the "high resolution" pixel resolution template is computationally inefficient due to the high angular resolution and the high spatial resolution of the pixel resolution template. To increase the computational efficiency of the system, one or more additional quantized angular templates and/or spatial templates based upon the pixel resolution template **140** are preferably utilized.

Referring to FIG. **6**, the edge orientations **120** may be quantized, such as, for example, into one of a set of six orientations, such as −15 to +15 degrees, +15 to +45 degrees, +45 to +75 degrees, +75 to +105 degrees, +105 to +135 degrees, and +135 to +165 degrees. The other opposing six orientations may not need to be determined because the system is preferably directionally invariant. Accordingly, each pixel of the pixel template **140** may be categorized as being within one of the six orientations forming an overall lower angular resolution template **150**.

Referring to FIG. **7**, to further increase the computational efficiency of the system, a lower spatial resolution template based upon the lower angular resolution template **150** may be defined by combing groups of pixels, including their angular orientations, into a combined angular direction at a lower resolution. The lower angular resolution template **150** may be modified in a manner to provide lower spatial resolution. For example, each block of 4×4 pixels of the lower angular resolution template may be combined to indicate a single direction and/or multiple directions. For each block of pixels, the frequency of the occurrence of each orientation may be arranged in a rank order. As an alternative, the orientations of the pixels in a block may be arranged in a rank order based on their associated edge strength and/or gradient magnitude. Then the top four occurrences (or other suitable number) of the ranked orientations may be selected as those orientations representative of those in the block. For example, if there are four different orientations then each of them may be selected. For example, if there are three orientations that are the same and a fourth orientation that is different, then the representative orientations may be the two different orientations. Likewise, the edge strength and/or gradient magnitude may be used as a basis for ranking. Other than being used as a basis of ranking to select the orientations, the frequency of the orientations (number of pixels having the same quantized orientation) is preferably not represented in the lower spatial resolution template.

Referring to FIG. **8**, to further increase the computational efficiency, the template may be encoded using a set of bytes, with bits of each byte being representative of an angular orientation. For example, the first bit may be representative of a first angular orientation of the six orientations. For example, the second bit may be representative of a second angular orientation of the six orientations. For example, the third bit may be representative of a third angular orientation of the six orientations. For example, the fourth bit may be representative of a fourth angular orientation of the six orientations. For example, the fifth bit may be representative of a fifth angular orientation of the six orientations. For example, the sixth bit may be representative of a sixth angular orientation of the six orientations. As previously noted, the angular orientations are preferably offset from horizontal and vertical, such as −15 degrees to +15 degrees, +15 degrees to +45 degrees, +45 degrees to +75 degrees, +75 degrees to +105 degrees, +105 degrees to +135 degrees, and +135 degrees to +165 degrees. Often the angular orientation of the object within the input image tends to have either vertical and/or horizontal edges, and generally centering those horizontal and/or vertical angular relationships within a range of angles (e.g., −15 to +15) tends to make the system more robust to slight angular modifications. With the potential angular relationships of groups of pixels being represented by bytes, the system can perform computationally efficient pattern matching.

Referring to FIG. **9**, in some cases it is desirable to include more robustness in the orientation of the angular determination for a particular pixel to reduce the effects of compared angles being on opposing sides of the quantized angular boundaries. For example, the model image may have an angle of 44 degree (bit pattern 00000100). However, the input image may have a local orientation angle of the same part of the object that was 46 degrees due to noise or other small changes. Then the angle of the input image would be quantized and given a bit pattern of 00001000. The angle codes would not match one another, even though there was only a very small difference in the orientation angle. In such cases with minor variations in the angle, the orientation of the angular determination between an input image and a model template may appear to be significant, while possibly only being different by a couple of degrees (e.g., 44 degrees and 46 degrees). To reduce this likelihood, the bit patterns of the model template may be broadened to include adjoining angular regions. Accordingly, if the bit pattern of the model image was modified to include both sides of the quantized region,

namely, 00001110, then the pixel region of the input image having a bit pattern of 00001000 would have overlap and thus be matched. In this manner, the matching would be more robust, although slightly less discriminative. This approach may be refined and extended using additional bit patterns. In particular, a bit pattern may be broadened on only one side of the quantized region, instead of both sides. Furthermore, the decision to broaden a bit pattern may be based on the proximity of the actual orientation angle to the quantization boundary.

Referring to FIG. **10**, to increase the computational efficiency of the system for input images that have objects therein that are at different angular orientations, the model image may be rotated to a plurality of different orientations. The templates are computed at each of the different angular orientations. In this manner, each of the templates for a particular model image may be pre-computed in an efficient manner. For example, the angular positions may include 0 degrees, 30 degrees, 60 degrees, 90 degrees, 120 degrees, and/or 150 degrees. In this manner, an input image to the system to be processed may be compared against a variety of pre-computed lower spatial resolution templates, and in particular, angularly quantized low resolution templates.

Referring to FIG. **11**, an exemplary model process **200** for a model image **210** and the input image process **230** are shown. The model image **210** may be pre-processed **212** to reduce noise in the image, such as using a low pass filtering operation. The filtered model image **212** may be rotated among a set of orientations, such as by 30 degrees, by a rotation module **214**. For each of the set of orientations **214** the system may compute the gradients to identify the edges within the image and determine those pixels of the image corresponding with the edges **216**. For each of the set of orientations for which the edges are determined **216**, the system may extract the orientations for each pixel and the dominant orientations for blocks of pixels (such as a 4×4 blocks of pixels) and store the result as a set of bytes having suitable bit patterns **218**, as previously discussed. In addition, the system may generate a set of full resolution templates at substantially finer angular resolutions, such as rotations of one degree. The result of this process is a set of model feature templates **220**.

The exemplary input image process **230** for an input image **232** may include being pre-processed **234** to reduce noise in the image. The system may compute the gradients to identify the edges within the filtered input image and determine those pixels of the image corresponding with the edges **236**. For each of the edges that are determined **236**, the system may extract **238** the orientations for each pixel and the dominant orientations for blocks of pixels (such as a 4×4 blocks of pixels) and store the result as a set of bytes having suitable bit patterns **240**, as previously discussed. The system may likewise compute a full resolution input feature images. The result of this process is input feature images **240**.

The system may compute template matching scores **250** between the input feature images **240** and each of the coarse rotations of the model feature templates **220** for different regions of the input image **232**. These comparison templates are preferably based upon the byte representation of the respective images, as previously discussed. For example, the system may process the templates centered at each pixel or block of pixels of the input image or otherwise in any other suitable manner. A set of matches **252**, preferably those with the highest scores, between the input feature images and the template is determined in any suitable manner.

The result of the matches **252** provides initial candidate locations in the input image that are likely to include an object of interest and also provide rough angular orientations of the objects of interest. The system then refines **254** the angular orientation of each of the objects of interest in the input image by using the course resolution model image at its finer angular resolutions to determine a finer angular estimation. In addition, the system may refine **254** the spatial location of each of the objects of interest in the input image by using the coarse resolution model image at its finer angular resolution. The input feature images may use a higher resolution and/or finer angular resolution, if desired. A set of refined matches between the input feature images and the templates are determined in a suitable manner.

The use of a two-stage matching process is computationally more efficient than a one-stage process. The first stage provides a rough estimation of the location of potential objects of interest in the input image, in an efficient manner. The second stage provides a finer estimation of the location of the identified potential objects of interest in the input image, in an efficient manner, by reducing the area of the search and the angular range of the search.

The result of the matching refinement **254** may be provided to a fractional refinement process **256**. The fractional refinement process **256** may include an angular search and/or a spatial search using the "full resolution" model image. Also, the fractional refinement process **256** may refine the angular orientation of the objects of interest in the input image by using the "full resolution" model image at angles interpolated in some manner between its finer angular resolutions to determine a fractional angular estimation. In addition, the fractional refinement process **256** may refine the spatial location of the objects of interest in the input image by using the "full resolution" model image at its finer angular resolution and/or fractional angle at positions interpolated in some manner. The input feature images may use a higher resolution and/or finer angular resolution template, if desired. A set of further refined matches **258** is determined in a suitable manner.

The use of a three-stage matching process is computationally more efficient than a one-stage or two-stage process. The first stage provides a rough estimation of the location of potential objects of interest in the input image, in an efficient manner. The second stage provides a finer estimation of the location of the identified potential objects of interest in the input image, in an efficient manner, by reducing the angular range of the search. The third stage provides a reduced spatial and/or angular search together with a sub-angular and/or sub-pixel resolution which provides a finer estimation of the location of the identified potential objects of interest in the input image, in an efficient manner.

In some cases it may be desirable to provide the ability to more accurately match the model image to the objects in the input image having different scales. The model feature templates are preferably determined at a single scale. The input feature images are preferably determined at a plurality of scales, which is more memory efficient than storing the model image at a plurality of scales. The system may rescale **260** the input image **232** to a different scale. Thereafter, a set of templates and object matching is performed on the rescaled input image **260**. The system determines if all scaled images are completed **262**, which if not, then the system rescales the input image **260** to a different scale. Generally duplicate matches may be omitted, if desired. When the system determines that all scaled images are completed **262**, then the system provides the matching objects and positions for each of the rescaled input images **264** which may be mapped back to the input image resolution.

Referring to FIG. **13**, a more detailed illustration of the refine objects at full resolution process **254** and the refine

object at fractional position and fractional angle process **256** are shown. The refine objects at full resolution process **254** may use a set of candidate angles in a local range around the current angle candidate and a set of candidate positions in a local rage around the current position. The angles and positions with the highest matching scores may be tracked. The refine object at fractional position and fractional angle process **256** may estimate a fractional sub-degree rotation angle **270**, generate a rotated template at the estimated fractional rotation angle **272**, compute matching scores for the rotated template at all candidate positions **274**, and estimate fractional sub-pixel object position **276**, to provide the object angle and position **258**.

Referring to FIG. **14**, one technique for estimating the fractional rotational offset is to assume that the peak score values locally behave as a quadratic function of the rotation angle. The peak scores at a set of discrete angles may be determined (e.g., s(−1), s(0), s(1)). The peak score may be estimated as $\{s(-1)-s(1)\}/2\{s(-1)+s(1)-2*s(0)\}$.

The sub-pixel refinement **256** may be performed in any suitable manner. Often the input to the sub-pixel refinement **256** is a score at each pixel and the location of a peak value. Thus the refinement technique may be based on a local score map around the course peak point.

A Barycentric weighting technique may use the score map values to weight each pixel in the local window to obtain the centroid of the neighborhood around the peak value. The Barycentric weighting technique is computationally efficient although tends to be limited to a linear fitting. This may be represented as:

$$x_c = \frac{\Sigma_i(x_i s_i)}{\Sigma_i x_i}$$

$$y_c = \frac{\Sigma_i(y_i s_i)}{\Sigma_i y_i}$$

A quadratic curve fitting technique fits a bi-quadratic curve to the pixels in the local window around the peak points. This uses a second order fitting which includes a least squares estimation of the error and produces two sets of three coefficients that may be used to reconstruct the curve and find the maximum. This fitting process may be improved by solving the linear equation sets by Hessian matrix and first order derivative. The result is the sub-pixel offset of the maximal point. Without lose of generality, the coarse peak point may be located at (0,0), which is the center of the local window of the score used for refinement. The model for the refinement may be:

$$f(x,y)=ax^2+by^2+cxy+dx+ey+g$$

Where

$$\frac{a^2 f}{a^2 x} = a$$

$$\frac{af}{ax} = 2ax + cy + d$$

$$\frac{a^2 f}{a^2 y} = b$$

$$\frac{af}{ay} = 2by + cx + e$$

The first order of x and y should be 0 at the peak point, then the equation set as follows as:

$$\begin{bmatrix} 2a & c \\ c & 2b \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} = -\begin{bmatrix} d \\ e \end{bmatrix}$$

The system may use the first and second derivative at the coarse peak point to approximate the coefficients a, b, c, d, and e to get the solution of x and y, which is the sub-pixel shift.

A Gaussian fitting technique may be used, such as using a two dimensional Gaussian plane model. The data in the score map is presumed to have a normal distribution. The system may use the first and second derivative at the coarse peak point to approximate the coefficients a, b, c, d, and e to get the solution of x and y, which is the sub-pixel shift. The Gaussian fitting may be represented as:

$$G(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} g^{-\left(\frac{(x-\mu_x)^2}{2\sigma_x}\right)+\left(\frac{(y-\mu_y)^2}{2\sigma_y}\right)}$$

The fitting objective is to find the proper $\sigma_x$, $\sigma_y$, $\mu_x$, $\mu_y$ to estimate the non-grid value. The $\mu_x$, $\mu_y$ are the results for Gaussian sub-pixel refinement. The fit procedure may use the Levenberg-Marquardt optimization technique for the local window.

The feature matching techniques of the system may be improved by identifying particular regions of the image that should be searched and/or otherwise particular regions of the image that should not be searched. The coarse searching requires a significant amount of computational time and a more computationally efficient initial matching criteria may be used to decrease the processing time of the subsequent coarse matching technique.

Referring to FIG. **15**, a pre-matching technique **290** may use those pixels identified as edge pixels to do an initial screening of areas of the input image. Pixels not identified as being part of an edge may be omitted as not being likely to be an object in the input image. Thus, the system primarily only performs a matching on the non-zero edge pixels. Thus, the matching technique may indicate candidate positions that are very unlikely to result in a good match, and thus may be skipped. Accordingly, positions that are likely to result in at least a reasonable match are considered in the coarse search stage. The pre-matching technique **290** may determine if the number of edge pixels in the model template is relatively close to the number of edge pixels within the potential object area in the input image. Due to the likelihood of some occlusions or partial objects, the input edge pixel count may at times tend to be smaller than the model edge pixel count. Accordingly, one suitable criteria could for the pre-matching technique **290** is as follows: input edge pixel count>=model edge pixel count*ratio. As it may be appreciated, the edge pixel count is a feature that is computationally efficient to determine and tends to be rotationally invariant. The result is a mask image that defines those regions that meet the pre-matching technique **290** criteria, thus reducing those regions of the image that should be matched during subsequent more computationally intensive processing.

In some cases, it may be more computationally efficient to perform the matching techniques at multiple down sampled resolutions. For example, the matching may be performed at image resolutions down sampled initially at a 4×4 block resolution. A threshold may be applied to the result to further reduce the regions to be searched. Then those areas of potential matching the matching may be performed at image resolutions down sampled at 2×2 block resolutions. Also, a

threshold may be applied to the result to further reduce the regions to be searched. In this manner, the coarse template matching may be performed in a computationally efficient manner. Downsampling the feature image may be performed very efficiently using bitwise operations. For example, the bitwise OR operation may be used to combine bit patterns corresponding to feature values of pixels in a 2×2 area.

In some cases, it is desirable to use a modified set of angular orientations for the search, rather than, 0 degrees, 30 degrees, 60 degrees, 90 degrees, 120 degrees, and/or 150 degrees. The selected spacing between the different orientations is preferably sufficiently small enough that the search technique does not miss a match, but likewise sufficiently large enough to make the matching technique computationally efficient. This determination may be based upon an auto-correlation between the original template and the rotated templates. The coarse angle search step may be selected based on the width of the main peak in the auto-correlation function. Computing and analyzing the rotational auto-correlation of the templates may be performed during an off-line stage. This enables adaptation of the angle search step to the specific object, such that the processing time is reduced for various objects.

Referring to FIG. **16**, an exemplary correlation graph is shown as a function of angular degree. It may be observed by selecting a sufficiently small range ensures that the peak will be determined. In contrast, if a sufficiently large range is selected then one or more of the minor peaks may be inadvertently selected.

In many cases, model images have sufficient symmetry that the system should employ a technique that only searches a range of approximately 180 degrees. The model image may be analyzed to determine if it is sufficiently symmetrical in some manner to be suitable for using a symmetrical technique. In the event the model image is not symmetrical, then a technique using generally a full 360 degree search range may be used. The analysis of symmetry of the object in the model image may be based on the auto-correlation of the model template. This analysis may be performed in an off-line stage. Searching a range of approximately 180 degrees during the coarse template matching stage reduces processing time, compared to searching a full range of 360 degrees. In some cases, the analysis may indicate that an object has more symmetry, such as 3 or 4 fold symmetry. In such cases, the search range may be reduced further below 180 degrees.

In some cases it is desirable to do a coarse matching technique followed by a refined matching technique. Then it is desirable to perform another refined matching technique in the opposite direction, such as at 180 degrees from the results of the first matching technique. Thereafter, the orientation with the better matching may be used for the sub-pixel sub-angular further matching refinement. For example, in the case that a reduced angular search is performed in a range of approximately 180 degrees instead of 360 degrees, it is desirable to perform an additional refinement stage in a small angle range around the angle 180 degrees opposite of the first refinement result.

While the compute template matching scores **250** performs an adequate matching function, it requires significant computational resources because of the large number of locations that need calculations to be performed with respect to the model feature templates **220**. In particular, the brute-force sliding window based technique of the aforementioned compute template matching scores **250** process requires significant computational resources. Moreover, regions of the input image which are not particularly relevant to the particular characteristics of the model image **210** are likewise processed for potential matches using the brute force technique, which is similarly computationally expensive. A more computationally effective technique that is suitable for the general template matching architecture is desirable that still maintains a discriminative feature set. A suitable approach to maintaining a discriminative feature set, while reducing the computational complexity, is to use a feature location index.

Referring to FIG. **17**, a modified system (1) for the input image process **230** receiving the input image **232** and (2) the model image process **200** receiving the model image **210** is illustrated. The model image process **200** includes an extraction of dominant orientations for each pixel and/or block **380** which may result in a modified model feature template **390**, if desired.

Referring also to FIG. **18**, to increase the computational efficiency, the extract dominant orientations **380** may be encoded using a set of bytes, with bits of each byte being representative of an angular orientation for a pixel and/or a block of pixels. For example, the first bit may be representative of a first angular orientation of six orientations. For example, the second bit may be representative of a second angular orientation of six orientations. For example, the third bit may be representative of a third angular orientation of six orientations. For example, the fourth bit may be representative of a fourth angular orientation of six orientations. For example, the fifth bit may be representative of a fifth angular orientation of six orientations. For example, the sixth bit may be representative of a sixth angular orientation of six orientations. The angular orientations may be aligned with the horizontal axis and vertical axis, such as +90 degrees to +60 degrees (e.g., 00000001), +60 degrees to +30 degrees (e.g., 00000010), +30 degrees to +0 degrees (e.g., 00000100), +0 degrees to −30 degrees (e.g., 00001000), −30 degrees to −60 degrees (e.g., 00010000), and −60 degrees to −90 degrees (e.g., 00100000). By ignoring the direction of the angular orientation, the remaining orientations may be as follows, such as, −90 degrees to −120 degrees (e.g., 00000001), −120 degrees to −150 degrees (e.g., 00000010), −150 degrees to −180 degrees (e.g., 00000100), +180 degrees to +150 degrees (e.g., 00001000), +150 degrees to +120 degrees (e.g., 00010000), and +120 degrees to +90 degrees (e.g., 00100000). In the case that there is no dominant orientation the system may assign 00000000 to that feature code value. In this manner, the sufficiently flat background areas of the image and/or those without with no dominant orientation will have 00000000 values as the feature code value. The division of the 360 degree range into the angular orientations may be rotated, as a whole, any desired amount. For example a suitable rotation may be 15 degrees from that shown in FIG. **18**. The bytes associated with particular angular orientations may be changed, as desired.

Referring also to FIG. **19**, to increase the ability to discriminate among finer orientations while not substantially increasing the coding complexity, the extract dominant orientations **380** may be encoded using a set of bytes, with multiple bits of each byte being representative of an angular orientation for a pixel and/or a block of pixels. In particular, a pair of bits may be used to signal a different angular orientation than each bit alone. For example, the first bit may be representative of a first angular orientation of six orientations. For example, the second bit may be representative of a second angular orientation of six orientations. For example, the third bit may be representative of a third angular orientation of six orientations. For example, the fourth bit may be representative of a fourth angular orientation of six orientations. For example, the fifth bit may be representative of a fifth angular orientation of six orientations. For example, the sixth bit may be representative of a sixth angular orientation of six orien-

tations. The angular orientations may be aligned with the horizontal axis and vertical axis, such as +90 degrees to +60 degrees (e.g., 00000001), +60 degrees to +30 degrees (e.g., 00000010), +30 degrees to +0 degrees (e.g., 00000100), +0 degrees to −30 degrees (e.g., 00001000), −30 degrees to −60 degrees (e.g., 00010000), and −60 degrees to −90 degrees (e.g., 00100000). By ignoring the direction of the angular orientation, the remaining orientations may be as follows, such as, −90 degrees to −120 degrees (e.g., 00000001), −120 degrees to −150 degrees (e.g., 00000010), −150 degrees to −180 degrees (e.g., 00000100), +180 degrees to +150 degrees (e.g., 00001000), +150 degrees to +120 degrees (e.g., 00010000), and +120 degrees to +90 degrees (e.g., 00100000). In the case that there is no dominant orientation, the system may assign 0000000 to that feature code value. The feature code values are, accordingly, 1, 2, 4, 8, 16, and 32.

The angular orientations may further be refined by pairs of bits, such as, such as +75 degrees to +45 degrees (e.g., 00000011), +45 degrees to +15 degrees (e.g., 00000110), +15 degrees to −15 degrees (e.g., 00001100), −15 degrees to −45 degrees (e.g., 00011000), −45 degrees to −75 degrees (e.g., 00110000), and −75 degrees to −105 degrees (e.g., 00100001). By ignoring the direction of the angular orientation, the remaining orientations may be as follows, such as, −105 degrees to −135 degrees (e.g., 00000011), −135 degrees to −165 degrees (e.g., 00000110), −165 degrees to +165 degrees (e.g., 00001100), +165 degrees to +135 degrees (e.g., 00011000), +135 degrees to +105 degrees (e.g., 00110000), and +150 degrees to +75 degrees (e.g., 00100001). The feature code values are, accordingly, 3, 6, 12, 24, 48, and 33, in addition to 1, 2, 4, 8, 16, and 32. The additional feature codes facilitate an increase in precision while maintaining a robust system. This multi-bit signaling technique provides the capability of more robustly signaling regions near the boundary between regions signaled by the single bit, without significant added complexity. The division of the 360 degree range into the angular orientations may be rotated, as a whole, any desired amount. For example a suitable rotation may be 15 degrees from that shown in FIG. **19**. The bytes associated with particular angular orientations may be changed, as desired.

Referring again to FIG. **17**, the dominant gradient orientations **380** may be stored as model feature templates **390**. The input image process **230** may receive the dominant gradient orientations **370** and/or the input feature templates **420** to construct a feature location index from dominant orientations **400**. Accordingly, each pixel location and/or block of pixels may have a corresponding feature code that is encoded in some manner. It is noted that other image features may be used, in addition to or in alternative to, the gradient orientation.

Referring to FIG. **20**, the feature location index **400** of the input image **232** may be a feature location list (h[**0**], . . . , h[**32**]) which stores a list of locations which belong to each feature. In this manner, the feature location index **400** includes a set of positions for each of the features, namely, 0, 1, 2, 4, 8, 16, and 32. Feature 0 may be omitted, if desired. For each of the features, a list of locations within the input image **232** that correspond with that feature are determined, such as by using the extracted orientations **370** and/or input feature template **420**. Accordingly, for each of the features of the index a corresponding list of locations within the input image that have that feature are collected. To further reduce the computational complexity and reduce the memory requirements, each of the spatial (x,y) locations within the list of locations may be stored as a single value, such as (x*image_height+y) or (x+y*image_width).

Referring again to FIG. **17**, the input image process **230** includes the extract dominant orientations for each pixel and/or block process **370** which may be stored as an input feature template **420**. The extract dominant orientations process **380** may use a corresponding technique to the extract dominant orientations process **370** used to build the feature location index **400**. In this manner, the feature characteristics of the model image **210** and the input image **232** may be expressed in a corresponding manner.

Referring to FIG. **21**, each feature value in the model feature template **390** may be matched by a compute matching scores process **410** with the feature location index **400**. The locations defined by the feature location index **400** are then accumulated by the compute matching scores process **410**. This process is repeated for each pixel and/or block of pixels of the model image **210**. The output of the compute matching scores process **410** is a set of matching scores **415**.

Referring to FIG. **22**, the spatial characteristics of the model feature template may be taken into account. For example, the model feature template may include four positions P**1**, P**2**, P**3**, P**4** with the spatial characteristics of a 2×2 array. The position P**1** may include feature index **1**, the position P**2** may include feature index **4**, the position P**3** may include feature index **1**, and the position P**4** may include feature index **8**. There are three corresponding locations in the input image with feature index **1** for position "P**1**" as identified by **500**A, **500**B, **500**C. There are three corresponding locations in the input image with feature index **4** as identified by **502**A, **502**B, **502**C which are accumulated in the matching scores process **410** by shifting one position to the left **504**A, **504**B, **504**C, to account for the spatial characteristics of position "P**2**" of the model feature template **390**. There are two corresponding locations in the input image with feature index **8** as identified by **506**A, **506**B which are accumulated in the matching scores process **410** by shifting diagonally one position to the upper left **508**A, **508**B, to account for the spatial characteristics of position "P**4**" of the model feature template **390**. There are three corresponding locations in the input image with feature index **1** as identified by **500**A, **500**B, **500**C, which are accumulated in the matching scores process **410** by shifting one position up to **510**A, **510**B, **510**C, to account for the spatial characteristics of position "P**3**" of the model feature template **390**.

Referring to FIG. **23**, the compute matching scores process **410** may accumulate the number of matches for the model feature template **390** at each of the pixels and/or blocks of the input image **232**. In this manner, the score map **415** with the accumulated totals is obtained, indicating the position of the likely matches within the input image. It is to be understood that any suitable position within the templates may be used as a reference for the spatial offset. It is also noted that the positions with a feature of 0 may be omitted. It is also noted that this feature template index technique may result in the same matching scores as the brute force sliding window based technique.

In the case that the input feature image generates a uniform distribution of locations for each feature index, the system may achieve generally six times the computational efficiency. Typically, the distribution of locations for each feature index varies, so it is more likely that the system may achieve generally three times the computational efficiency. Furthermore, a significant amount of computational complexity is reduced by omitting locations where the index is 0, and at the same time, the system does not need any coarse-to-fine searches.

It is also to be understood that in some embodiments at least one of the angular orientations for the edge pixels of the input image and/or input feature template may map to a

plurality of the feature indexes. It is also to be understood that in some embodiments at least one of the angular orientations for the edge pixels of the model image and/or model feature template may map to a plurality of angular orientations for the matching. It is also to be understood that in some embodiments at least one of the angular orientations for the edge pixels of the input image and/or input feature template may map to a plurality of the feature indexes and at least one of the angular orientations for the edge pixels of the model image and/or model feature template may map to a plurality of angular orientations for the matching.

The system may use a plurality of model templates, each of which likely corresponds with a separate angular orientation and/or view of the model image. In this manner, a set of matching scores may be determined for each of the model images, and thus for each of the angular orientations. An iterative process of feature extraction and matching over a plurality of templates may be used to generate an updated angle map and/or score map. This enables the system to select a template, or interpolate between templates, to more accurately match the objects in the input image. However, in either case, the feature location index is constructed a single time from the input image, which decreases the computational complexity of the system. This plurality of templates may correspond to multiple views of the same object or may correspond to views of multiple, different, objects.

The terms and expressions which have been employed in the foregoing specification are used therein as terms of description and not of limitation, and there is no intention, in the use of such terms and expressions, of excluding equivalents of the features shown and described or portions thereof, it being recognized that the scope of the invention is defined and limited only by the claims which follow.

We claim:

**1**. A method for image processing, said method comprising:

(a) a computing device, labeling edge pixels of a model image using an edge based technique;

(b) said computing device, specifying an angular orientation for each of said edge pixels of said model image, wherein a plurality of pixels of said model image are labeled as non-edge pixels and do not have an angular orientation specified;

(c) said computing device, labeling edge pixels of an input image using an edge based technique;

(d) said computing device, specifying an angular orientation for each of said edge pixels of said input image;

(e) said computing device, indexing each of said angular orientations for each of said edge pixels of said input image into a feature index identifying its respective location wherein said respective location is stored as a one-dimensional value in a location list, where the one-dimensional value preserves a two-dimensional said location;

(f) said computing device, determining candidate locations of an object within said input image based on said feature index and said angular orientation for each of said edge pixels of said model image, and including identifying said candidate locations in a coarse resolution stage that identifies for at least one block of pixels a predetermined number of top-ranked said angular orientations, ranking made by a criteria that includes at least one of:

(i) the frequency of the occurrence of a said angular orientation in a block of pixels;

(ii) the strength of an edge associated with a said angular orientation; and

(iii) a gradient magnitude of an edge associated with a said angular orientation

where the top-ranked said angular orientations are used to define a low resolution template, and where the candidate locations are modified in a fine resolution stage using at least one high resolution template; and

(g) based upon the modified said candidate locations selecting at least one object location within said input image.

**2**. The method of claim **1** wherein a plurality of pixels of said input image are labeled as non-edge pixels and do not have an angular orientation specified.

**3**. The method of claim **1** wherein said angular orientations of at least one of said model image and said input image are defined relative to a reference angle as, +90 degrees to +60 degrees, +60 degrees to +30 degrees, +30 degrees to +0 degrees, +0 degrees to −30 degrees, −30 degrees to −60 degrees, −60 degrees to −90 degrees, −90 degrees to −120 degrees, −120 degrees to −150 degrees, −150 degrees to −180 degrees, +180 degrees to +150 degrees, +150 degrees to +120 degrees, and +120 degrees to +90 degrees.

**4**. The method of claim **3** wherein said reference angle is 15 degrees with respect to a horizontal axis.

**5**. The method of claim **1** wherein said angular orientations of at least one of said model image and said input image are represented relative to a reference angle as, +90 degrees to +60 degrees as 00000001, +60 degrees to +30 degrees as 00000010, +30 degrees to +0 degrees as 00000100, +0 degrees to −30 degrees as 00001000, −30 degrees to −60 degrees as 00010000, −60 degrees to −90 degrees as 00100000, +90 degrees to +60 degrees as 00000001, +60 degrees to +30 degrees as 00000010, +30 degrees to +0 degrees as 00000100, +0 degrees to −30 degrees as 00001000, −30 degrees to −60 degrees as 00010000, 60 degrees to −90 degrees as 00100000, −90 degrees to −120 degrees as 00000001, −120 degrees to −150 degrees as 00000010, −150 degrees to −180 degrees as 00000100, +180 degrees to +150 degrees as 00001000, +150 degrees to +120 degrees as 00010000, and +120 degrees to +90 degrees as 00100000, −90 degrees to −120 degrees as 00000001, −120 degrees to −150 degrees as 00000010, −150 degrees to −180 degrees as 00000100, +180 degrees to +150 degrees as 00001000, +150 degrees to +120 degrees as 00010000, and +120 degrees to +90 degrees as 00100000.

**6**. The method of claim **5** wherein said reference angle is 15 degrees with respect to a horizontal axis.

**7**. The method of claim **1** wherein said angular orientations of at least one of said model image and said input image are represented relative to a reference angle as at least four different angular orientations, each of which substantially span the same angular range.

**8**. The method of claim **1** wherein said angular orientations of at least one of said model image and said input image are represented relative to a reference angle as, +75 degrees to +45 degrees as 00000011, +45 degrees to +15 degrees as 00000110, +15 degrees to 45 degrees as 00001100, 45 degrees to −45 degrees as 00011000, −45 degrees to −75 degrees as 00110000, −75 degrees to −105 degrees as 00100001, −105 degrees to −135 degrees as 00000011, −135 degrees to −165 degrees as 00000110, −165 degrees to +165 degrees as 00001100, +165 degrees to +135 degrees as 00011000, +135 degrees to +105 degrees as 00110000, and +150 degrees to +75 degrees as 00100001.

**9**. The method of claim **5** wherein said angular orientations of said at least one of said model image and said input image are further represented relative to said reference angle as, +75 degrees to +45 degrees as 00000011, +45 degrees to +15

degrees as 00000110, +15 degrees to −15 degrees as 00001100, −15 degrees to −45 degrees as 00011000, −45 degrees to −75 degrees as 00110000, −75 degrees to −105 degrees as 00100001, −105 degrees to −135 degrees as 00000011, −135 degrees to −165 degrees as 00000110, −165 degrees to +165 degrees as 00001100, +165 degrees to +135 degrees as 00011000, +135 degrees to +105 degrees as 00110000, and +150 degrees to +75 degrees as 00100001.

**10**. The method of claim **1** wherein determining candidate locations of an object within said input image is based upon spatial characteristics of said model image.

**11**. The method of claim **1** wherein at least one of said angular orientations for said edge pixels of said input image map to a plurality of said feature indexes.

**12**. The method of claim **1** wherein at least one of said angular orientations for said edge pixels of said model image map to a plurality of angular orientations for said matching.

**13**. The method of claim **1** wherein at least one of said angular orientations for said edge pixels of said input image map to a plurality of said feature indexes and at least one of said angular orientations for said edge pixels of said model image map to a plurality of angular orientations for said matching.

**14**. A method for image processing comprising:

(a) a computing device determining edge pixels of a first model template and a second model template using an edge based technique, said first model template and said second model template being rotated versions of a single model image;

(b) said computing device determining an angular orientation for each of said edge pixels of said first model template and said second model template;

(c) said computing device determining edge pixels of an input image using an edge based technique;

(d) said computing device determining an angular orientation for each of said edge pixels of said input image;

(e) said computing device indexing each of said angular orientations for each of said edge pixels of said input image into a feature index identifying its respective location;

(f) said computing device determining candidate locations of an object within said input image based on said feature index and said angular orientation for each of said edge pixels of said first model template and said second model template, using a single score map;

(g) based upon said candidate locations selecting at least one object location within said input image.

* * * * *

UNITED STATES PATENT AND TRADEMARK OFFICE

# CERTIFICATE OF CORRECTION



PATENT NO. : 9,269,023 B2
APPLICATION NO. : 13/484758
DATED : February 23, 2016
INVENTOR(S) : Hae-Jong Seo and Petrus J. L. van Beek

It is certified that error appears in the above-identified patent and that said Letters Patent is hereby corrected as shown below:

In the Claims

**Col. 14, Lines 34-35**

**Change** "-60 degrees as 00010000, 60 degrees" **to read** -- -60 degrees as 00010000, -60 --;

**Col. 14, Lines 56-57**

**Change** "00000110, +15 degrees to 45 degrees as 00001100, 45 degrees to -45 degrees as 00011000, -45 degrees to -75" **to read** -- 00000110, +15 degrees to -15 degrees as 000011000, -15 degrees to -45 degrees as 00011000, -45 degrees to -75 --.

Signed and Sealed this
Twenty-sixth Day of July, 2016

Michelle K. Lee

Michelle K. Lee
*Director of the United States Patent and Trademark Office*